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Monitoring Motion of Pigs in Thermal Videos

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Abstract. We propose a new approach for monitoring animal movement in thermal videos. The method distinguishes movements as walking in the expected direction from walking in the opposite direction, stopping or lying down. The method utilizes blob detection combined with optical flow to segment the pigs and extract features which characterize a pig's movement (direction and speed). Subsequently a multiway principal component analysis is used to analyze the movement features and monitor their development over time. Results are presented in the form of quality control charts of the principal components. The method works on-line with pre-training.

Keywords: Optical flow, blob detection, multiway principle components, quality control.

1 Introduction

Animal well-being has become a concern for consumers and [1] suggests that the stress level of pigs before slaughter influences meat quality. To ensure animal well-being the pigs should be constantly monitored and in case of a stressful situation actions should be taken. However it is difficult to keep track of many animals and therefore some automated behavior analysis methods should be implemented. For this paper, pigs were filmed in a constrained area walking from left to right. However, some pigs can change direction or stop walking. Such events can block the movement of other pigs. There can be different reasons for the change in movements such as not feeling good or an obstacle appeared in the path. The classification is challenging, because it is quite normal for pigs to slow down or even stop to sniff for no reason but out of curiosity.

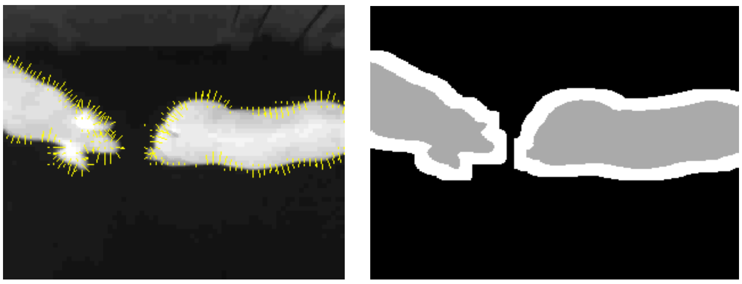
The automated video analysis will allow the slaughter house to make sure all animals are walking in order and intervene when necessary. It is important, that the analysis provides a fast overview of the area with easily interpretable results. No animal crowd monitoring and analysis methods have been suggested in the literature. Previous research has mainly focused on analyzing human crowd behavior in surveillance videos. A good overview of the methods can be found in [2]. The choice of method greatly depends on the video type and what we are looking for in the videos. There are methods available for tracking individual objects, usually used for pattern search in movements. However, in our thermal videos it is very complicated to identify the individual pigs because of physical similarities and the fact that each pig does not necessarily appear in many frames. Therefore we instead propose to use optical flow which often is used for object tracking and action recognition. This method gives a great overview of the surveillance area.

2 Methodology

In this section the methodology is presented in details. It takes two distinct steps to perform the analysis. In the first step, the visual analysis is performed using optical flow, blob detection and optical flow quantification. The second step is the behavioral analysis based on quality control charts. Here multiway PCA is performed and quality control chats are built for the principal components.
We used different sections from 5 thermal videos. In total 2460 frames were available for training. For testing representative sections from 2 thermal videos were extracted with a total of 2284 frames. To validate the test results the 2284 frames were manually annotated and classified.

2.1 Visual Analysis

As mentioned above we are not just interested in detecting moving pigs but also the stationary ones. To do so we merged two methods: optical flow and blob detection. First optical flow is applied and then filtered by a simple threshold to remove the noise. The threshold is half of the overall average length of the vectors from optical flow. The results of this step for one frame are shown in Figure 1.



(a) Optical flow. (b) Blob detection.

Fig. 1: Visual analysis step. First we calculate optical flow and then use blob detection. In (b) grey represents the actual blobs and white represents blobs extended by 5 pixels.

To separate those optical flow vectors representing pigs from the background we created a binary mask using morphological erosion and opening. These are

particularly convenient as both are obtained as by-products of optical flow. Alternatively a simple threshold could be used. All blobs were extended by 5 pixels to include the vectors along the edges in the further analysis.
For each frame two histograms were used to quantify optical flow. The first represents the lengths of the optical flow vectors and the second the angles. The number of bins were selected by

2.2 Quality Control

Multiway PCA is used in batch monitoring in statistical process control[3] . Investigating the quality of a current batch requires historical data of good batches. Data consist of repeated measurements monitored throughout the process. A collection of batches can be presented in 3D matrix and a special unfolding technique to a 2D matrix will allow to apply ordinary PCA. By monitoring the score plots of principal components it is possible to track changes in the process.
For multiway PCA application on thermal videos we need to define what we mean with "the batch". We use the concept of a scene: a constant number of consecutive frames in a video is a scene. The number of frames per scene was found by minimizing the prediction sum of squared residuals (SSE) on a training set including all PC.

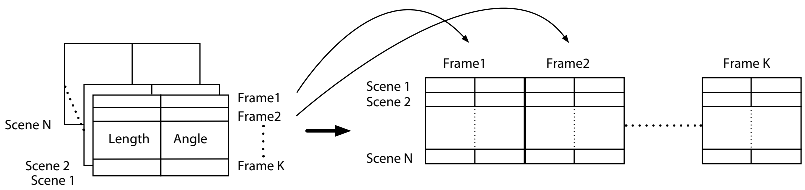


Fig. 2: Unfolding the data matrix.

As it was mentioned above a special unfolding technique has to be performed such that the ordinary PCA can be applied. Let$N$ be the number of scenes and K the number of frames in each scene. Each frame is represented by the counts from the two histograms which are stacked next to each other. The unfolding is done by reshaping the scene to a row vector, i.e. the K frames of a scene are stacked after each other as shown in Figure 2. All the unfolded scene vectors are stacked on top of each other forming the final matrix. Let J be the total number of bins per frame, then the unfolded matrix has the dimension $N \times JK$. This unfolding technique allows for comparison among scenes.
A score matrix t, loading matrix p and residual matrix E were obtained after performing PCA on the unfolded matrix. R is the number of principal components. Let X be unfolded matrix then it can be presented as:

$$X = \sum_{r=1}^{R} t_r \otimes p_r + E \tag{1}$$

In statistical quality control a training state is usually called phase I. In this phase we collect good scenes, build a quality control chart and check if all our scenes are statistically in control. The control limits used in this phase are different from the limits used in the second phase. In [4] they suggest three methods for checking good batches. First Hotelling's T2 statistics:

$$D_s = t'_R S^{-1} t_R \frac{I}{(I-1)^2} \sim B_{\frac{R}{2}, \frac{I-R-1}{2}, \alpha} \tag{2}$$

where $S \in \mathbb{R}^{R \times R}$ is an estimated covariance matrix and B is a beta distributed random variable. The second test is a sum of square of residuals of individual batches:

$$Q_i = \sum_{k=1}^{K} \sum_{j=1}^{J} E(i, kj)^2 \tag{3}$$

For the third test the PCA scores are used. Score plot of the first two principal components and confidence internals are used to identify outliers. The confidence intervals are ellipsoids with center at $\mathbf{0}$ and axis length:

$$\pm S(r, r) B_{1, \frac{I-2-1}{2}, \alpha} \sqrt{\frac{(I-1)^2}{I}} \tag{4}$$

In phase II we perform on-line monitoring. For the on-line monitoring new confidence intervals for the score plot must be calculated:

$$\pm S(r, r) F_{2, I-2, \alpha} 2 \sqrt{\frac{I^2 - 1}{I(I-2)}} \tag{5}$$

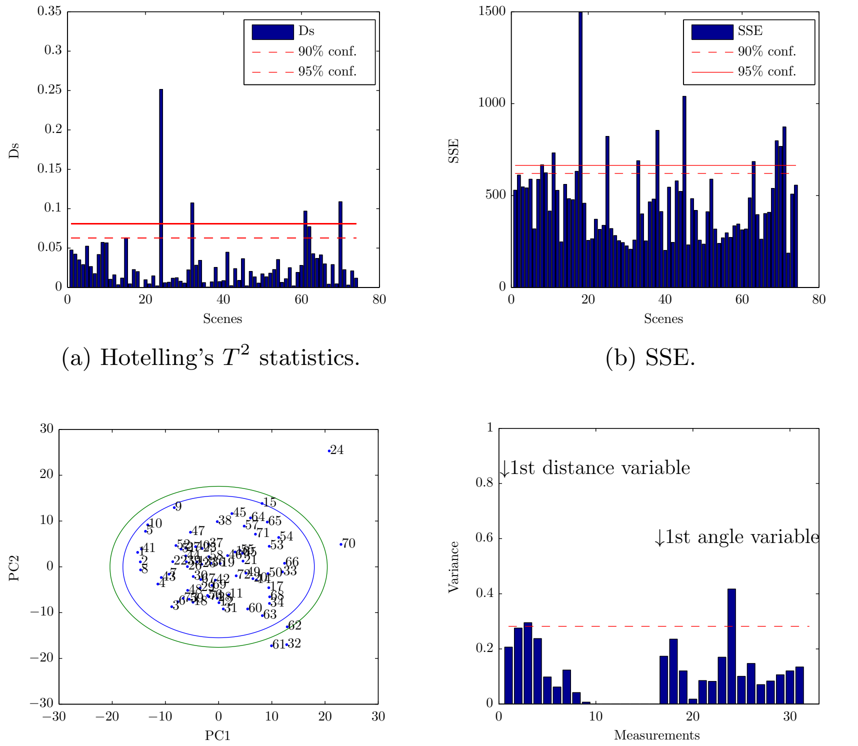
A visual analysis was done for every frame when on-line monitoring had started. Every set of 25 frames form a scene which is transformed into a score through the multiway PCA. The score is added to the quality control chart. [3] suggests not waiting for all measurements from a batch but to estimate the remaining batch measurements. However, there is no reason to do so here since a scene only requires 25 frames, thus control chart is updated every few seconds.

3 Results

As mentioned above, two phases are required to perform the analysis of thermal videos. In this section results of each phase will be discussed.

3.1 Phase I

Figure 3 shows Hotelling's T^2 statistics (a) and SSE (b) for every scene, and the scores of the two first principle components (c). The first two principal components were chosen naively as Hotelling's T^2 statistics combines the PCs equally weighted causing increased misclassification when including additional



(a) Hotelling's T^2 statistics.

(b) SSE.

(c) Score plot.

(d) Explained variance by each variable.

Fig. 3: Training data.

components. Analyzing many plot is not an option as well, because the aim is to give an easy to interpret overview of the video. These three plots all have points exceeding the confidence interval thus indicating that there might be some outliers. However, after inspecting each scene no unusual behavior was noticed. Figure 3(d) shows the explained variance by each of the 32 variables. The most important variable is the 8th variable from the angle histogram. This bin represents vectors with the smallest angles. A small angle is when pig is walking straight. The second most important variable is the 3rd bin of speed. The faster the pigs are going the heavier the tail of the speed histogram will be.

3.2 Phase II

Each of the 2284 frames were manually annotated as not moving if at least one pig was not moving. A scene was declared as not moving if more than half of the frames were annotated as not moving. Table 1 shows that 66% of all scenes were classified correctly and at the individual frame level 78% of all frames were classified correctly. As it can be seen in Figure 1 most of the errors appeared very close to the limits. It is important to remember, that it is very difficult to annotate movements just by looking at a single frame or even a sequence of frames. Some errors could appear due to annotation.

Annotated \ Classified	Moving	Not moving
Moving	17	8
Not moving	21	36

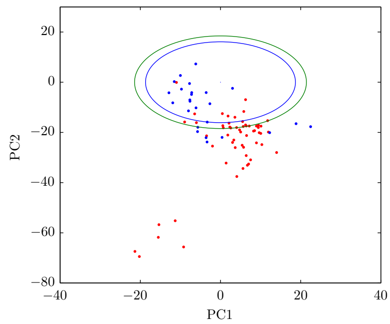


Table 1: Results of phase II.

4 Conclusion

Our suggested method can classify 66% of scenes and 78% of the frames correctly. It is difficult to get higher results due to the complexity of annotation. Also some pigs may slow down to sniff around but this situation should not be considered as not moving. However, these situations will create additional variance.
Future improvements could be to analyze clusters or individual pigs and new methods for vector quantification. In scenes with many pigs and lots of action some details can get lost in the histograms.
With better quantification of the optical flow vectors it would be possible to determine some patterns of behavior or actions through classification based on score plots.

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